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Trace -Based Model in Knowledge Acquisition System for Valuing Knowledge

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Abstract

Aims: This paper presents a trace-based model in Knowledge Acquisition System for Valuing Knowledge. In Case Based Reasoning (CBR), solving problems is based on the solutions of similar past problems. From the system's point of view, this might be true, but from the user's point of view, identical problems may need different solutions. This is due to that (CBR) suffers from the "frame problem": in some situations, the context information is missing. Moving from the Case-Based Reasoning to Trace-Based Reasoning (TBR) is the solution of this problem. Trace-Based Reasoning is an extension of the Case-Based Reasoning, allowing the context to be included in the reasoning.
Study Design: The model includes three related stages in solving problems; the first is context – aware retrieved information stage and the second is tracing the user tasks in order to cover all the needed elements in the environment of the given problem. The third stage is the implicitly processed via a back propagation feature exists in the neuro-fuzzy module.
Place and Duration of Study: Evaluation and Analysis of Hospital Disaster Preparedness in Jeddah for six months.
Methodology: There are six factors have been utilized in the Adaptive Neural Fuzzy Inference module that covers the second stage (Task Analysis Module) of the proposed system alongside with the back propagation process. The training will be based on gathered surveyed data. The purpose of the training is to adjust the model parameters, particularly the input membership function parameters, and the corresponding output values.
Results: After training the model with proper data, a clear target-oriented towards the best usage of knowledge will take a place. The developed six modules for the second stage with different types of input/output membership functions and trained an input array. The modules are compared based on their ability to train with lowest error values. The Gaussian membership function input with either constant or linear pairing output membership function was the best choice for the proposed system to be adopted in its second stage which is Task Analysis Module.
Conclusion: This model can be utilized in firms, societies or even in individuals' life events. The context of knowledge as one of the six factors affecting the knowledge valuation process is the most important factor due to its high changes were more noticeable than others.

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1 Introduction

Solving problems is one of many tasks that are strongly related to the survival of human being. There are many methods for solving problems and there are many differences between these methods used from different perspectives and factors such as the kind of the problem, the domain and the problem space. Considering the problem space representation, it was found that most of the problem solving methods relying on the problem space representation will depend even if slightly on similar problem solved or observed in past experience [1].

Case-based reasoning is one of the methods in solving problems that all reasoning is based on past cases personally experienced. But depending only on the past experience is not enough to solve some problems, what makes a main problem of the case-based reasoning to appear is the lack of relevant context information in the problem space to be considered in solving new problems [3,4]. A macro model presented [2], states that how important the context-aware systems are in supporting learning processes. An example of such systems is the "The Knowledge Maturing Process" with its five stages shown in Fig. 1.

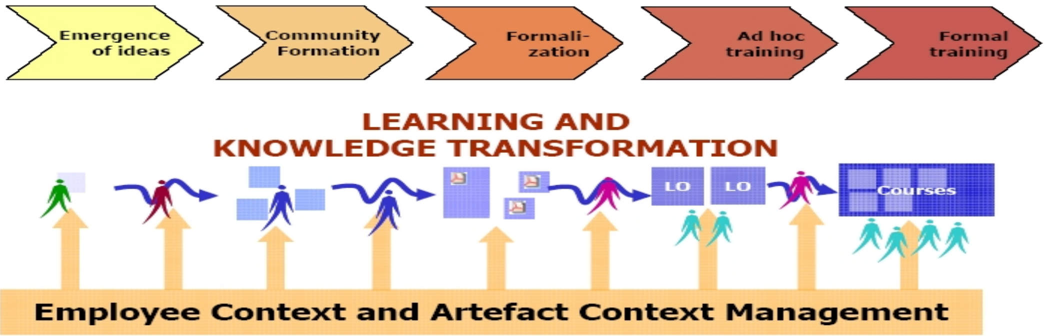


Fig. 1. The knowledge maturing process [2]

The main important conclusion obtained from this model is that by determining the considered context and relevant artifacts, the system can help the learner in making best use of existing pieces. Therefore, the proposed model in this research work will focus on how to identify the relevant context information and how to use it efficiently.

According to the definition of Case-Based Reasoning (CBR), solving problems is based on the solutions of similar past problems [3]. The Case-Based Reasoning suffers from the “frame problem”: in some situations, the context information is missing.

Other researchers have addressed how useful the contextual retrieved information in search queries [5] they stated that one of the key factors for accurate and effective information access is the user context. The critical elements that make up a user's information context include the semantic knowledge about the domain being investigated, the short-term information need as might be expressed in a query, and the user profiles that reveal long-term interests.

The concept of "trace" refers to a record of "something" that has occurred in the past. A trace is a "footprint": what remains of a phenomenon after it has ended. In computer sciences, traces are everywhere (log files, navigation history, versioning, etc.) and have been studied for several purposes (personalization of interfaces, information retrieval, human-computer interactions analysis, etc.). The theory of traces refers to various techniques described in [18]. Recently, several researchers have contributed to the elaboration of a trace theory [19]. According to this theory, a trace is a set of temporally and spatially situated elements that are inscribed in the environment during an activity. One should observe that a trace is inscribed intentionally or not.

Moving from the Case-Based Reasoning to Trace-Based Reasoning (TBR) is the solution of this problem but this actually will lead to many different problems to be identified as following:

1. How to identify the relevant context information in trace-Based Reasoning?
2. How to make sure all the elements we need are in the trace and then use them by an efficient model to solve the faced problems.
3. How to utilize this proposed framework in valuing knowledge in a firm or in an organization, by transferring the intangible factors that are needed to valuate knowledge in an organization into numbers, in order to help understanding how an organization's knowledge adds value to its operations and thus enabling informed management of its knowledge assets.

2 Methodology

There are many factors expressed for the purpose of knowledge valuation ontology. As per [6], six factors will be used to valuing knowledge. These factors will be utilized an Adaptive Neural Fuzzy Inference System (ANFIS) that covers the second stage of the proposed model alongside with the back propagation process.

The first stage will include context-aware retrieval information algorithm. These stages will be used for valuing knowledge. There are five kinds of components used to specify knowledge in ontology's: concepts, relations, functions, axioms and instances. The aim of knowledge valuation ontology is allowing the users to express factors relevant to valuing a particular chunk of knowledge.

Fig. 2 presents the structure and main processes of the model. The proposed model is based on managing the knowledge valuation via the affecting of different factors in order to getting the desired value of the available knowledge.

2.1 Inference Network

In this stage; context retrieval information algorithm has been used which integrates the essential elements of user's information context. In this algorithm the user' context is represented taking into account the user's short-term and long-term profiles, as well as relevant concepts from a pre-existing ontology [5]. In their framework, the user's "context" is captured via nodes in a concept lattice induced from the original ontology and is updated incrementally based on user's interactions with the concepts in the ontology. Their experimental results showed that utilizing the user context improves the effectiveness of the search queries, especially in the typical case of Web users who tend to use very short queries. .A term-vector based representation is used for concepts. To generate a term-vector representation, the content of all the associated relations with the concept are combined to yield a single term-vector. To convert the problem space from ordinary space to convex space λ will be used here, in addition to generalize the normal spaces. A weighted term-vector its symbol is ni for each concept i. Each concept contains a collection of relations R_i, and a set of sub-concepts S_i .To compute n_i, first we compute a term-vector n_R for each element $r \in R_i$. Then n_i is computed as the following:

$$ni=(1-\lambda) \sum_{r \in R} n_r + \sum_{s \in s} ns$$

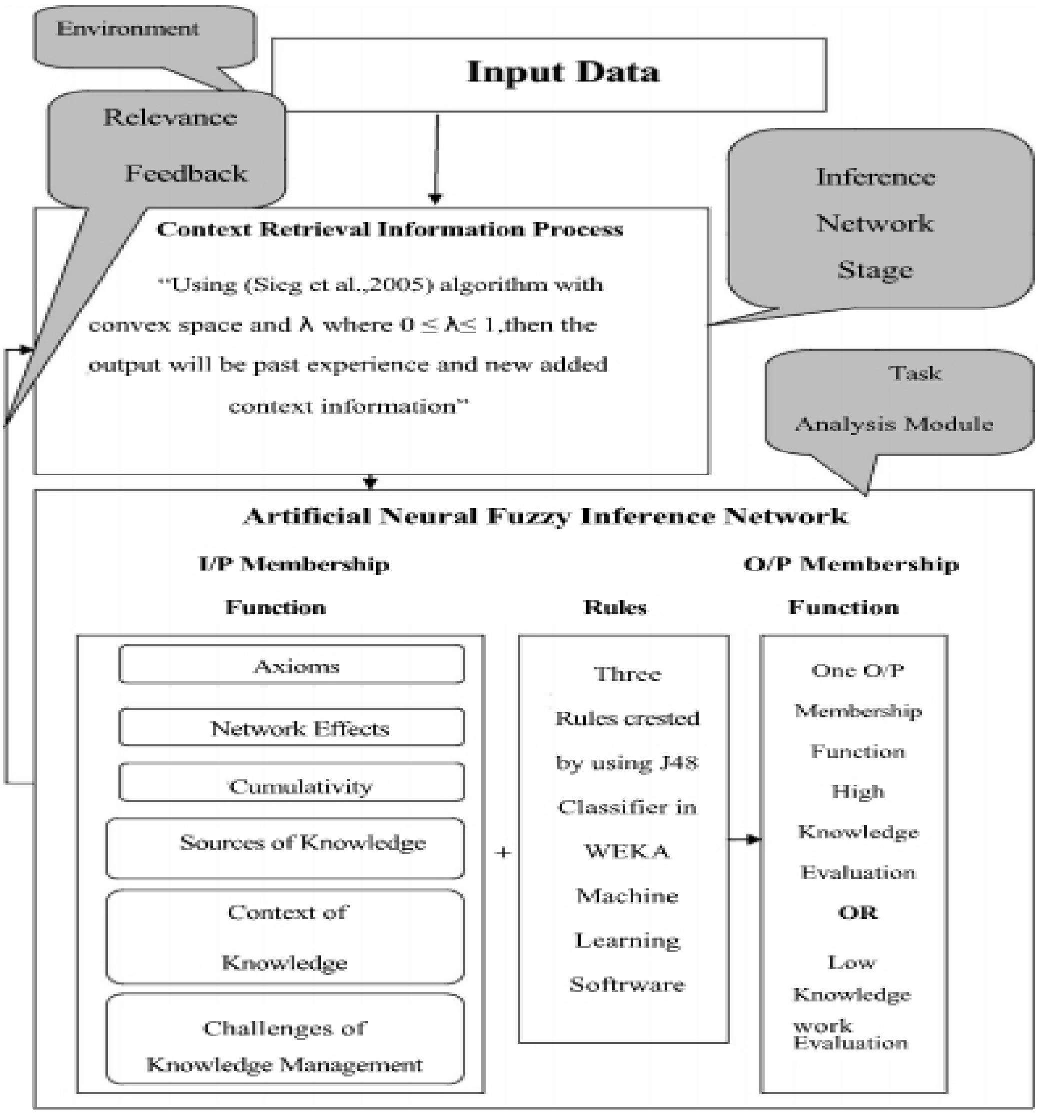


Fig. 2. The Structure and main processes of the model

where each n_s is a term-vector for each sub-concept $s \in S$ and $0 \leq \lambda \leq 1$.

Let $n_1 = \{w^1_1, w^1{}_2, w^1{}_3 \ldots w^1{}_k\}$ and $n_2 = \{w^2_1, w^2_2, w^2{}_3 \ldots w^2_k\}$ be two nodes in the problem space .Then $n1 \leq n2$ if and only if $\forall$ $wj1 \leq wj2$, where wji is the weight of a term j in the term vector for n. The operations on these nodes are summarized in the selection and de-selection of these nodes, depending on the user query or on the stored profile for the user. Selection and de-selection operations are translated to vector operations min and max operations, respectively as per the following:

$$\min(n_1,n_2) = \{\min(w^1{}_1, w^2{}_1), \ldots \min(w^1{}_k, w^1{}_k)\}$$

and

$$\max(n_1,n_2) = \{\min(w^1{}_1, w^2{}_1), \ldots \max(w^1_k, w^1{}_k)\}$$

When $\lambda = 1$ then the sub-concept will be the main content for the term vector n_i and when $\lambda = 0$ both relations and sub-concepts will be included in each n_i . Thus the user context is represented as a pair of elements:

ci = {P,N} ,where P is a term-vector of positive evidence (min operation) : P = min(n1 ,n2),and N is a term vector of negative evidence (max operation) : N = max(n1,n2).The min and max operations could be extended to more logical operations intersection and union operations, respectively. Thus, the positive evidence will be represented as $P = n1 \cap n2 \cap n3 \cap \ldots nk$ and the negative evidence will be represented as N = n1 U n2 U n3 U …. nk.

Each time the user interacts in the specific domain seeking more information, the user's short term interest as a context c_i , which is a pair of positive and negative evidence. In order to represent the user term context, i.e. the user profile as a set of contexts: pr = {0, c1, c2.....,cn}. Depending on user behavior, a specific context in the user profile can be updated or a new context can be added.

Via this algorithm solving the faced problems have been transferred from the Case Based Reasoning approach to Trace Based Reasoning approach, which in terms achieving one of the aims of this work. The user's context information represented by user's short term and long term profiles, in addition to the past pre-existing ontology, are fed as inputs for the next stage of the model which is Task Analysis Module.

2.2 Task Analysis Module

In this stage, there will be an implementation of the model of Artificial Neural Fuzzy Inference System (ANFIS) via using linguistic variables represented by membership functions (mf) indicating the degree and the status of each factor on the process of valuing knowledge. These six factors are described in details in the following subsections:

2.2.1 Axioms

As per [6]'s comment cited from Fox and Gruninger,1999,p.111 that retrieval of information not directly stored in the data base does not require wider search characteristic if ontology's stored the means for relatively straightforward deductions within themselves, i.e. by using axioms. There are five kinds of components used to specify knowledge in ontology's: concepts, relations, functions, axioms and instances. Axioms are model sentences that are always true. Their existence in ontology is to constrain its information, verify its correctness or deduce new information [7].

Table 1 illustrates one of the developed methodology which is an ontology-supported literature search that is specified in the Web Ontology Language OWL DL [8].Tools have been employed for automated textual analysis to produce a set of document annotations, which was then manually evaluated. Six distinct annotation sets S1 to S6 using different annotation methods for 2,289 logical axioms.

The results of this methodology was that the decision space (means keeping tracking of the dependencies between axioms) saved about 75% of reasoned calls and the appropriate choice of axioms leads to a better performance [9].

Table 1. Shows revision results for OWL DL Axiom Ontology

		S_1 (54, 94%)			**S_2 (60, 100%)**	
Impact $^+$	69%	4,677	36,773	83%	2,584	18,702
Guaranteed	48%	11,860	51,677	65%	8,190	55,273
Impact $^-$	9%	17,828	46,461	12%	20,739	67,625
Upper bound	74%	4,110	11,399	83%	2,645	27,850
Random	45%	-	1,291	60%	-	1,090
		S_3 (40, 45%)			**S_4 (35, 48%)**	
Impact $^+$	20%	3,137	26,759	29%	2,198	15,601
Guaranteed	43%	3,914	27,629	43%	3,137	18,367
Impact $^-$	28%	9,947	46,461	31%	7,309	10,217
Upper bound	48%	3,509	13,202	51%	2,177	7,002
Random	31%	-	764	31%	-	534
		S_5 (26, 26%)			**S_6 (72, 12%)**	
Impact $^+$	8%	1,778	11,443	13%	9,352	212,041
Guaranteed	39%	1,290	6,647	54%	8,166	99,586
Impact $^-$	54%	954	1,438	76%	6,797	16,922
Upper bound	54%	801	1,989	76%	5,219	19,861
Random	41%	-	212	57%	-	1,065

2.2.2 Network effects

Network effects are characteristic of advanced technology and information based sectors of the economy. The more a piece of knowledge is used, the more valuable it is [6].The added value in every incident of networking lies in its contributions to the knowledge of the participants and to the enhancement of its value to them [10].

The Research and Development (R&D) is one of a corporate activity, as a mutually beneficial formal relationship between two or more parties, i.e. via network activities for increasing the stock of knowledge Fig. 3 Shows the strong correlation between patents and the Research and Development (R&D).

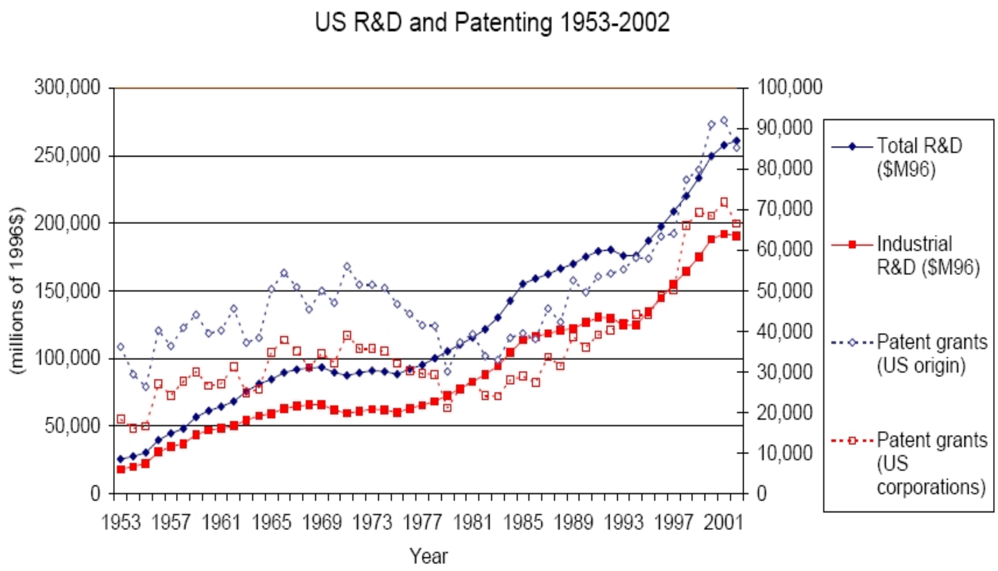


Fig. 3. Shows R and D and Patenting Time Series Relationship [11]

Referring to the World Intellectual Property Organization (WIPO) Indicators in 2010 and as shows that the direct proportional relationship between patent applications across the world versus years (1985 – 2008) as seen in Fig. 4. The overall percentage growth rate was positive through years excluding some slowdown periods had been occurred due to the global economic decline in that time which was in 2008.

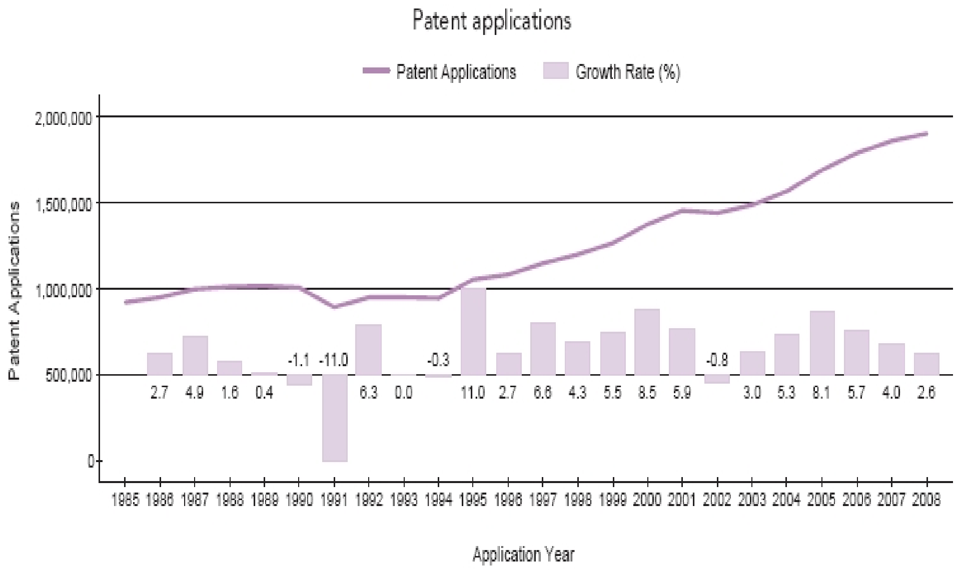


Fig. 4. Shows trend in total patent applications across the world

2.2.3 Cumulatively

To understand and acquire a chunk of knowledge is strongly influenced by other chunk of knowledge that is related to its [6]. Jeffrey, Furman & Stern [12] mentioned that the cumulative nature of the knowledge is recognized as central to economic growth. Using the cumulative nature of innovation development in the semiconductor industry, an analysis was achieved indicating how much new innovative outputs (patents) are based on already existing technological knowledge. Table 2 shows the correlation coefficient for each year which was calculated at first by calculating the intensity of each technological combination, and then correlating the combination vector of each year with the observations of the previous year [13].

Table 2. Shows revision results for OWL DL axiom ontology [9]

Year	Cumulativeness	Year	Cumulativeness
1963	.5288	1980	.9195
1964	.7443	1981	.8862
1965	.8288	1982	.8971
1966	.8532	1983	.8802
1967	.8581	1984	.8940
1968	.8621	1985	.9245
1969	.8713	1986	.9359
1970	.8731	1987	.9439
1971	.8873	1988	.9353
1972	.8777	1989	.9442
1973	.8538	1990	.9575
1974	.8716	1991	.9684
1975	.8917	1992	.9746
1976	.9057	1993	.9723
1975	.8917	1994	.9737
1976	.9057	1995	.9793
1977	.9006	1996	.9822
1978	.9074	1997	.9899
1979	.8982	1998	.9816

The ranges of the high or low effects of the cumulatively factor which will be figured out later in the paper were depending on the number of patents and patent growth in semiconductor technology space as shown in Fig. 5 for each year mentioned in Table 2.

2.2.4 Sources of knowledge

Sources of knowledge are the fourth factor affecting the valuation process of the knowledge. Referring to intellectual capital Stewart's definition mentioned in [14]: "the intellectual material – knowledge, information, intellectual property, experience – that can be put to use create wealth". According to the intellectual capital, there are three sources of knowledge assets: External Capital, Human Capital and Structural Capital [6]. A questionnaire obtained by a research team in Amsterdam 1999 from four companies: Institution of Higher Education, High-Tech Firm, Petroleum Exploration & Production Firm and Energy Delivery, has resulted in the chart shown in Fig. 6 for indicating the usefulness of each (Human, Structural and External (Customer)) capital in each of the four samples of companies [15].

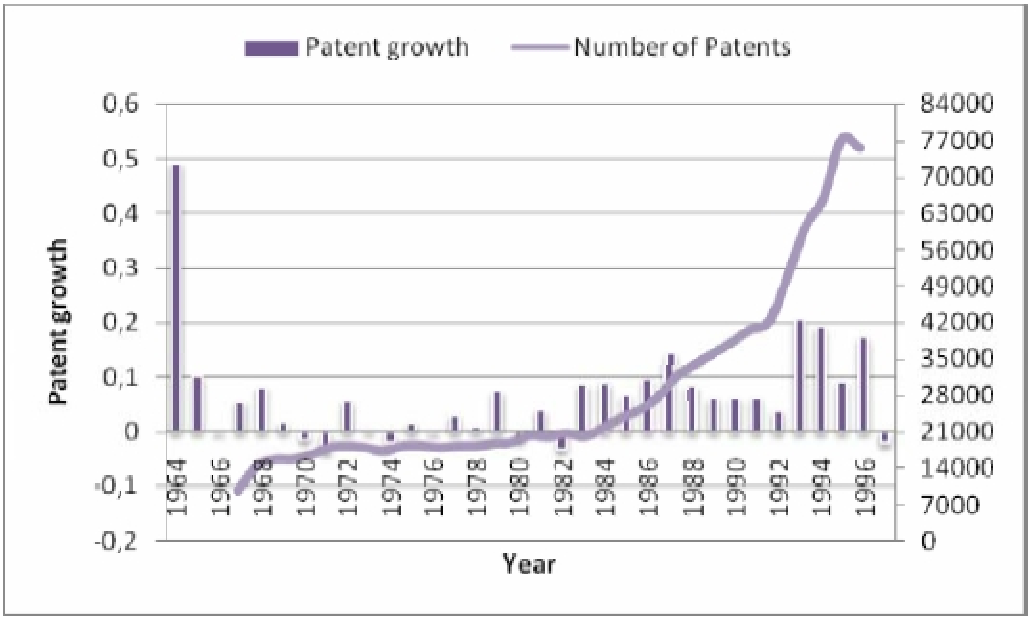


Fig. 5. Shows the evolution of the patents and patent growth in semiconductor technology space [13]

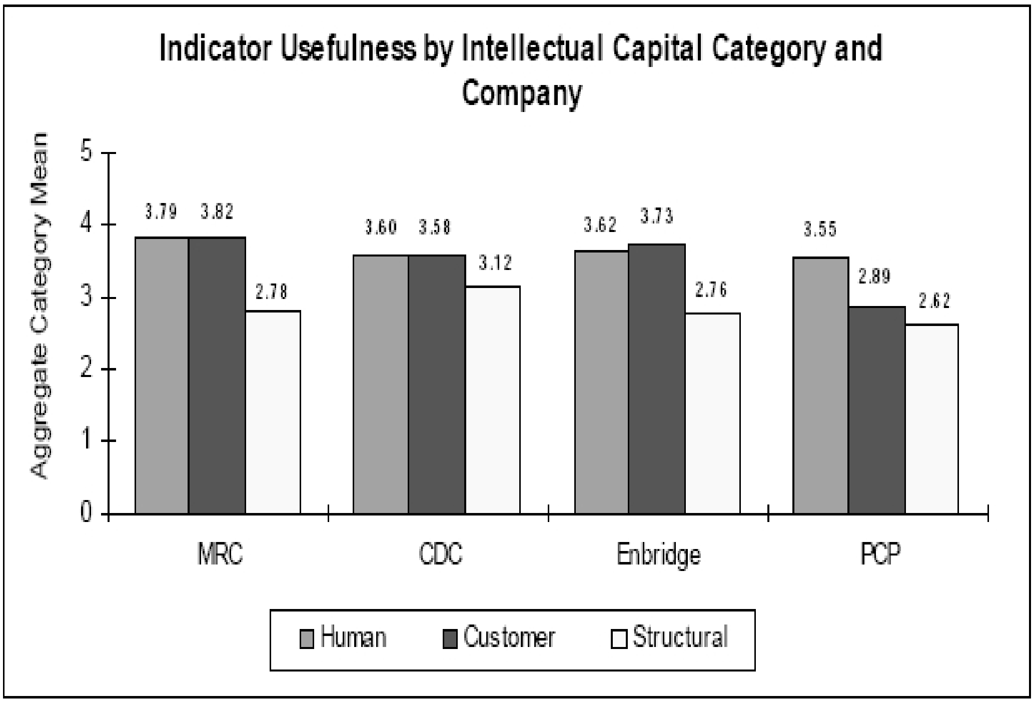


Fig. 6. Shows the intellectual capital types effect on four sample firms [15]

2.2.5 Context of knowledge

Knowledge's context refers to circumstances or events that come from the environment within which something exists or takes place. Because of this relation between knowledge and these circumstances, they have their effects on improving and valuating knowledge [16]. By referring to a questionnaire had been adopted for the purposes of an organization's information management practices, information behavior and values, and information uses.

Table 3 shows the questionnaire items for this survey. For the purposes of studying the effects of the context of knowledge on knowledge valuation process, we have focused on the Knowledge Management Environment (KME) items only which are listed in the Table 3 (as seen in column 2, which are KME1, KME2, KME3 and KME4), and Table 4 presents the analyzing their impact after observing the values of convergent validities of the four previously mentioned items with both Organizational Information Behavior (OIB) and Personal Information Behavior (PIB), which are defined as context or environment that nurtures behaviors at both organizational and personal levels.

Table 3. Shows matrix of loadings and cross-loadings of the survey's items

Custom	Item	Statement
KME	KME1	My organization has a culture intended to promote knowledge and information sharing.
	KME2	Knowledge and information in my organization is available and organized to make it easy to find what I need.
	KME3	Information about good work practices, lessons learned, and knowledgeable persons is easy to find in my organization.
	KM4	My organization makes use of information technology to facilitate knowledge and information sharing.
OIB	OIB1	The people I work with regularly share information on errors or failures openly.
	OIB2	The people I work with regularly use information on failures or errors to address problems constructively.
	OIB3 (Reversed)	Among the people I work with regularly, it is normal for individuals to keep information to themselves.
PIB	PIB1	I often exchange information with people with whom I work regularly.
	PIB2	I often exchange information with people outside of my regular work unit but within my organization.
	PIB3	I often exchange information with citizens, customers, or clients outside my organization.
	PIB4	I often exchange information with partner organizations.

Table 4. Analysis of the impact of values observed

	KME	PIB	OIB	Age	Sex	Job Category	Sex Job Category	Years in Org.
KME1	0.797	0.161	0.341	-0.052	-0.062	-0.103	-0.041	-0.045
KME2	0.832	0.151	0.267	0.000	-0.121	-0.089	-0.097	-0.080
KME3	0.838	0.175	0.398	0.008	-0.128	-0.121	-0.067	-0.075
KME4	0.806	0.209	0.297	-0.002	-0.070	-0.067	-0.047	-0.020
PIB1	0.259	0.680	0.342	0.020	0.027	0.096	0.058	-0.027
PIB2	0.089	0.720	0.116	0.194	0.085	0.139	0.082	0.152
PIB3	0.121	0.782	0.055	0.227	0.213	0.310	0.282	0.129
PIB4	0.142	0.758	0.132	0.163	0.082	0.129	0.079	0.176
OIB1	0.323	0.151	0.871	-0.018	-0.123	-0.125	-0.132	-0.166
OIB2	0.363	0.241	0.879	-0.050	-0.032	-0.074	-0.049	-0.118
OIB3	0.343	0.165	0.757	-0.087	-0.017	0.101	0.018	-0.057
Age	-0.014	0.209	-0.061	1.000	0.009	0.005	-0.002	0.534
Sex	-0.119	0.150	-0.072	0.009	1.000	0.478	0.884	0.152
Job Cat	-0.120	0.243	-0.041	0.005	0.478	1.000	0.602	0.235
Sex Job Cat	-0.077	0.187	-0.065	-0.002	0.884	0.602	1.000	0.202
Years In Org	-0.068	0.140	-0.135	0.533	0.152	0.235	0.202	1.000

2.2.6 Six challenges of knowledge management

Knowledge Management has the following challenges:

- Knowledge acquisition
- Knowledge modeling
- Knowledge retrieval
- Knowledge reuse
- Knowledge publishing
- Knowledge maintenance [6]

The effect of knowledge acquisition challenge will be used in terms of Knowledge Management effect on knowledge valuation process. A survey achieving this purpose had been undertaken consisting of 930 Greek companies; this study identified and discussed the critical success factors or enablers that determine the Knowledge Management effectiveness within organizations, which in turn influence the total performance of the firm [17,18,19].

Table 5 shows the construct validity and variance extracted for each of the factors listed to obtaining the survey's purposes mentioned above. We have focused on the last item which is Knowledge Management effectiveness for this paper. The calculation of the construct reliability of each factor leads the researcher to conclude whether or not the various items of a construct as a set are reliable, in the sense of producing similar construct metrics every time is used by different researchers for similar contexts [17,18,19].

Table 5. Shows construct reliability and variance extracted for survey's items

Items	λ_{ii}	ε_{ii}	λ_{ii}^2
Leadership			
LED1	0.79	0.38	0.6241
LED2	0.49	0.76	0.2401
LED3	0.53	0.72	0.2809
LED4	0.37	0.47	0.5329
	2.54	2.33	1.6780
0.73 construct reliability			
0.49 variance extracted			
Culture			
CUL1	0.32	0.90	0.1024
CUL2	0.83	0.31	0.6889
CUL3	0.86	0.25	0.7396
CUL4	0.89	0.20	0.7921
CUL5	0.80	0.36	0.6400
	3.70	2.02	2.9630
0.87 construct reliability			
0.59 variance extracted			
Strategy			
STR1	0.87	0.24	0.7569
STR2	0.92	0.16	0.8464
STR3	0.85	0.27	0.7225
	2.64	0.67	2.3258
0.91 construct reliability			
0.78 variance extracted			
Technology			
TEC1	0.75	0.44	0.5625
TEC2	0.45	0.80	0.2025
TEC3	0.57	0.68	0.3249
TEC4	0.69	0.53	0.4761
TEC5	0.71	0.50	0.5041
TEC6	0.51	0.73	0.2601
	3.68	3.68	2.3302
0.79 construct reliability			
0.39 variance extracted			
PEP1	0.41	0.83	0.1681
PEP2	0.41	0.83	0.1681
PEP3	0.84	0.30	0.7056
PEP4	0.93	0.13	0.8649
	2.59	2.09	1.9067
0.76 construct reliability			
0.48 variance extracted			
KM Effectiveness			
KM1	0.98	0.04	0.9604
KM2	0.89	0.21	0.7921
KM3	0.80	0.36	0.6400
KM4	0.68	0.54	0.4624
KM5	0.69	0.52	0.4721
KM6	0.85	0.27	0.7225
	4.89	1.94	4.0535
0.92 construct reliability			
0.68 variance extracted			
Firm Performance			
KMF1	0.85	0.27	0.7225
KMF2	0.93	0.13	0.8649
	1.78	0.40	1.5874
0.89 construct reliability			
0.80 variance extracted			

3 Implementations and Results

In this section; there will be an overview of the practical results obtained after submitting an ANFIS editor by using MATLAB for the input and out membership functions plus J48 Classifier by using the machine learning software.

3.1 Neuro-Fuzzy Models

Combining the ANN features and Fuzzy Logic rules, the Hybrid ANFIS system was presented and has been used frequently in modeling and solving problems in computer science and other related fields, past few decades have seen a resurgent trend towards establishment of intelligent manufacturing systems which are capable of using advanced knowledge-bases and intelligence techniques in aiding critical operational procedures in manufacturing. A particular architecture of neuro-fuzzy systems is that of the Adaptive Neuro Fuzzy Inference System (ANFIS) introduced by [20]. Fuzzy inference system used in ANFIS and it is composed of four functional blocks.

The knowledge base block contains database and rule base. Database defines the membership functions and rule base consists of fuzzy if-then rules. Fuzzifications interface which transforms the crisp inputs into degrees of match with linguistic values; a defuzzification interface which transforms the fuzzy results of the inference into a crisp output. The fuzzy rules used in ANFIS are of Takagi-Sugeno type. This type of fuzzy rule has fuzzy sets involved only in the premise part; the consequent part is described by a non-fuzzy equation of the input variables.

The fuzzy model for all the input factors and the output valuation is shown in Fig. 7. The models are done using MATLAB ANFIS editor with the input membership functions of Gaussian Bell.

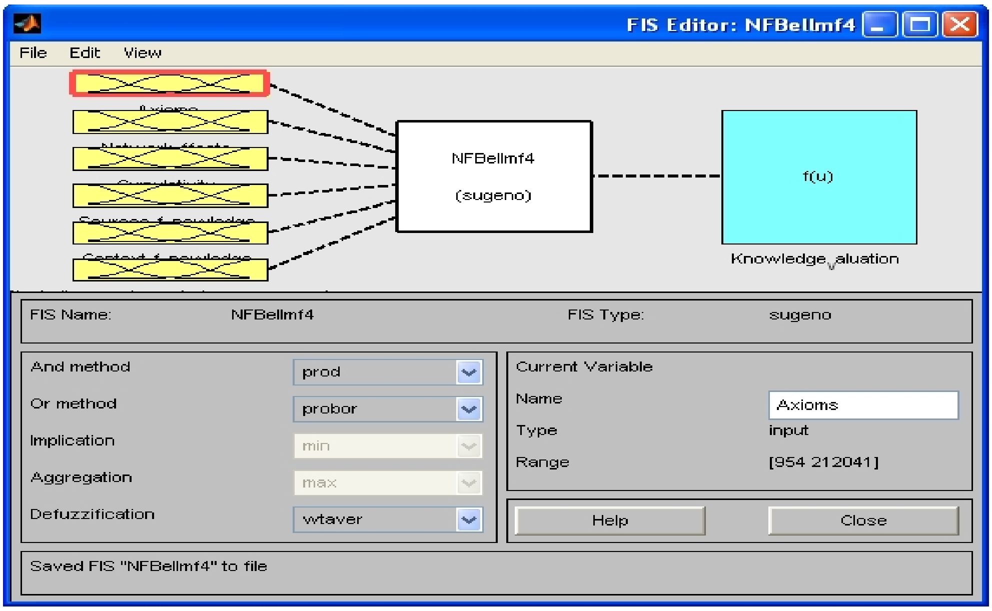


Fig. 7. Fuzzy model of the 6 input mfs

MATLAB ANFIS editor supports only the Sugeno type, and the Fuzzy Inference System (FIS) supports two types of output functions types, the constant, and the linear function. The rule in Sugeno fuzzy model has the form:

If (input 1 = x) and (input 2 = y) then output z = ax +by +c.

For the constant Sugeno model, the output level z is constant c, where a = b = 0. The output level zi of each rule is weighted by firing strength wi of the rule. Six distinct neuro-fuzzy models are used to demonstrate the correlation and delectability of knowledge valuation using the 6 factors presented earlier. The classifications of the models are given in Table 6. Each model is characterized by the type of the input/output membership functions and constant or linear output type.

Table 6. Model Specifications

Model Name	Input membership function	Output membership function
Generalized Bell	Gbellmf	Constant
Generalized Bell	Gbellmf	Linear
Gaussian	Gaussmf	Constant
Gaussian	Gaussmf	Linear
Gaussian2	Gauss2mf	Constant
Gaussian2	Gauss2mf	Linear

For each of the models shown in Table 6, we build the neuro-fuzzy structure. The structure of the J48 rules based neuro-fuzzy model is shown in Fig. 8.

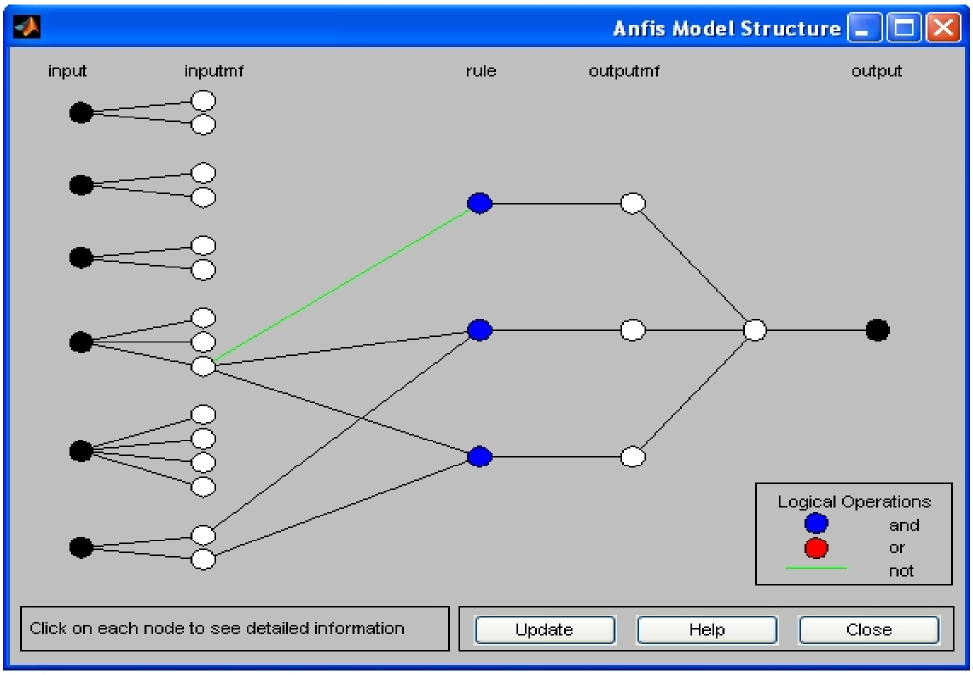


Fig. 8. Shows the Structure of the j48 rules based neuro /fuzzy model

3.2 Training

The purpose of the training is to adjust the model parameters, particularly the input membership function parameters, and the corresponding output values. The adjustment and tuning depend on the accuracy of the training data, as will be shown later.

Training needs two kinds of arrays, the first is the training array and the other one is the testing array. A training array is a two dimensional array [m×n], where (m) is the number of rows containing input values, and (n) is the number of input factors plus one for the output column. In our model, n = 7 since there are 6 distinct input variables and one output variable. Each row of the array contains some of the possible values for each input corresponding to the first n-1 columns representing the 6 variables, and the last column holds the desired output values. The testing array holds the data in the same way as the training array, but the data in this array is more accurate than the data of the training array.

The possible combinations for 6 inputs variables and 2 output values. Each input factor has on the average two linguistic variables, thus making the total combinations = 26, which equal to 64. The training array used was having m = 64 and n= 7 containing randomly chosen data, but has been constructed according to the rules obtained via J48 classifier in WEKA which is a machine learning software written in Java, contains a collection of visualization tools and algorithms for data analysis and predicting modeling, with an easy to use graphical user interface.

Using Cross Validation (10 folds): Here is the confusion matrix of J48 classifier. 60% data was used for training and 40% for testing and the data is selected randomly. Here it shows only the 40% of the testing data.

```
=== Confusion Matrix ===

 a b   <-- classified as
 5 4 | a = High
 3 7 | b = Low
```

Fig. 9. The confusion matrix using cross validation from WEKA program (snapshot)

The confusion matrix shows that 12 instances were correctly classified out of 19 and 7 instances were incorrectly classified. In other words, here 5 High values and 7 Low values are correctly classified and 4 High values and 3 Low values are incorrectly classified. 7 instances are miss classify because the classification is done by applying rules so there is may be an article which is according to the rules in class High but in actual it is in class Zero. So according to our system it is a miss classified article because our system has done classification according to the rules. The performance of J48 classifier is 63 %.

Using Percentage Split: The classification was also done by using the percentage split.

```
=== Confusion Matrix ===

 a b   <-- classified as
 0 0 | a = High
 2 4 | b = Low
```

Fig. 10. The confusion matrix using Percentage Split from WEKA program (snapshot)

The level of performance achieved by using percentage split is a little higher than the cross validation 66.6 % the results shows that 4 instances were correctly classified and 2 instances were wrongly classified.

The inputs that are having the strong influence on the result are included in the rules. In other word it could be said that these are the inputs which influence the classification results. The rules obtained are as follows:

1. If (Sources of Knowledge is Low) then (Knowledge Valuation) is Low.
2. If (Sources of Knowledge is High) and (Six Challenges of Knowledge Management is High) then (Knowledge Valuation) is High.
3. If (Sources of Knowledge is High) and (Six Challenges of Knowledge Management is Low) then (Knowledge Valuation) is High.

In order to figure out the effects of the six factors we did the following: for Axioms factor in knowledge valuation, two linguistic variables are created to implement the impact of axioms in valuing knowledge namely Axioms high impact (HighI) and axioms low impact (LowI).AHighI values range from 954 to 20,739 reasoner calls and ALowI values range from 1,438 to 212,041 reasoner calls, please refer to Table 1. Thus all other six factors have been figured out form each survey or data related and presented above..

3.3 Membership Functions of Input and Output Factors

The results of these training processes are shown below in Table 7 and in brief the first model of Generalized Bell function/Constant the only factors have been affected after training are: Axioms, Network Effects and Context of Knowledge. For linear output for the same input function (Generalized Bell) only Context of Knowledge has been affected. For the Gaussian function with either constant or linear output then, no changes have been resulted and an example of the six factors showing this result is Context of Knowledge as shown below in (2) in Table 7. Finally for the Gaussian2 function with either constant or linear output, also as in Gaussian function, no changes have been resulted, an example showing this result is Context of Knowledge in (3) in Table 7.

3.4 Results

We have measured the impact of training array on the performance of the models. In particular, we observe the error rate of the models under same numbers of epochs which is 800 epochs. An epoch in the ANFIS is one full cycle staring from the application of input at layer 1 of the model, until the firing weight of the rule is adjusted. At the end of an epoch, the error, which is defined as the difference between the desired output and the computed output value, is measured. The models are trained by using testing array its inputs have been chosen carefully.

Table 7. Results of training the six example models

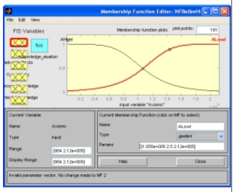
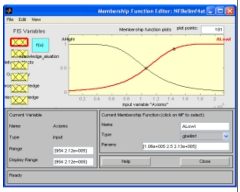
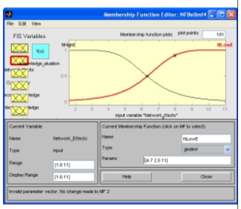
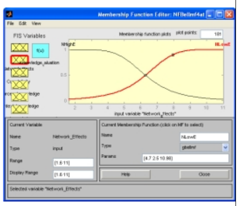
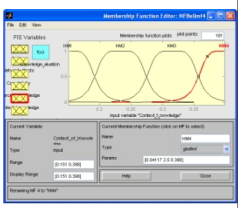
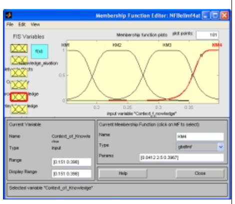
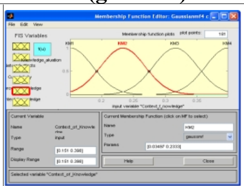
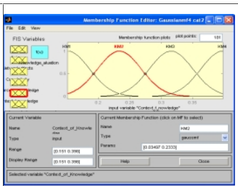
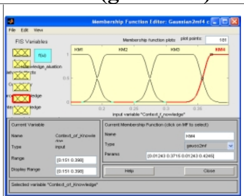
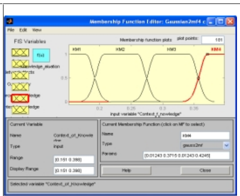
1. Generalized Bell function (gbellmf)/Constant				
Input	**Before Training**	**After Training**	**Parameters values before training**	**Parameters values after training**
AXIOMS (ALowI)			a = 1.055e+005 b = 2.5 c = 2.12e+005	a = 1.06e+005 b = 2.5 c = 2.12e+005
Network Effects NLowE			a = 4.7 b = 2.5 c = 11	a = 4.7 b = 2.5 c = 10.98
Context of Knowledge KM4			a = 0.04117 b = 2.5 c = 0.398	a = 0.04117 b = 2.5 c = 0.3967
2. Gaussian function (gaussmf)/Constant or Linear				
Context of Knowledge KM2			σ = 0.03497 C = 0.2333	σ = 0.03497 C = 0.2333
3. Gaussian2 function (gauss2mf)/Constant or Linear				
Context of Knowledge KM4			σ_1 = 0.03497 C_1= 0.2333 σ2 = 0.03497 C_2 = 0.2333	σ_1 = 0.03497 C_1= 0.2333 σ2 = 0.03497 C_2 = 0.2333

Table 8 shows the different values of the average testing errors for the three used membership functions (generalized bell, Gaussian, Gaussian2).

Table 8. Error values after testing the models for constant/Linear models

Model Name	Number of Epoch	The value of Error
Generalized Bell/Constant/Linear	800	0.46043
Gaussian/Constant/Linear	800	0.45846
Gaussian2/Constant /Linear	800	0.4641

4 Conclusion

The following can be conclude during the design and implementation of a Knowledge Acquisition System for valuing knowledge using with three stages, The first stage has been deduced from a previously existing algorithm which has achieved the purpose of converting the case based reasoning to trace based reasoning :

1. The second stage has been built by using a neuro-fuzzy model feeds by 6 factors. Each of these factors has been translated into membership functions reflecting their degree in impacting the process of valuing knowledge. ANFIS editor is a digital data processing in the computer and needs figures to work and have results. Although of these factors are being intangible ones but by surveys and questionnaires in the needed field, they have been figured out.
2. The fuzzy rules used and deducted by using a machine learning software written in Java called WEKA. The models were trained and the output parameters representing knowledge valuation can be adjusted using an array of training data. The results presented in this study show that knowledge can be valued using a neuro-fuzzy model. The performance of the model is measured in terms of error value obtained between the expected outputs. The experiments in this study were conducted using MATLAB neuro-fuzzy tool. The experiments show that the model is sensitive to the choice of input membership functions.
3. The Gaussian function is the most optimal in terms of trainability and producing low error values (see Table 8) results. In plus the choice of Sugeno either linear or constant output function is convenient accompanied to the Gaussian function.
4. The context of knowledge as one of the six factors affecting the knowledge valuation process is the most important factor due to its high changes were more noticeable than others (see Table 7) results for KM4 (1) the context of knowledge inputs and other results for KM1 has the parameter c value changed from (0.151) before training to (0.1503) after training and KM2 has the parameter c changed from (0.2333) before training to (0.2307) after training for the same model which is Generalized Bell / Constant Model, while the other factors for the same model showed results without changes after training . Context of information in terms and Trace Based Reasoning are both very important to be used in solving any faced problems.

Competing Interests

Authors have declared that no competing interests exist.

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